# Intraday return predictability: Evidence from commodity ETFs and their related volatility indices

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## ARTICLE INFO

## ABSTRACT

Using high-frequency data of crude oil, gold, and silver exchange-traded funds (ETFs) and their related volatility indices, we analyse patterns of intraday return predictability, also called intraday momentum, in each market. We find that intraday return predictability exists in all the markets, but the patterns of predictability differ for each market, with different half-hour returns, not necessarily the first half-hour returns of the trading day, exhibiting significant predictability for their last half-hour counterparts, depending on the specific market. The intraday return predictability is stronger on days of higher volatility and larger jumps. Substantial economic value can be generated by a market timing strategy which is constructed upon the intraday momentum, in all the markets under study. Possible theoretical explanations for the intraday return predictability are infrequent portfolio rebalancing investors and late-informed investors.

## 1. Introduction

There is growing body of literature on stock return predictability, which advocates that stock prices can be predicted based on the informational content of past returns (e.g., Rouwenhorst, 1998; Griffin et al., 2003; Moskowitz et al., 2012). However, the related literature mostly uses low frequency data. With the emergence of electronic trading platforms and the availability of intraday high-frequency data, day trading has become a popular trading activity over the last two decades. Day trading can be quite lucrative if profitable opportunities are captured by trading algorithms. Accordingly, day traders are keen to understand whether intraday high-frequency data exhibits evidence of intraday predictability, also called intraday momentum. In contrast to the high availability of day trading data, limited research dealing with return predictability based on intraday data has been carried out. The pioneering work of Gao et al. (2018) considers the US stock market and finds evidence that the first and penultimate half-hour returns exhibit positive forecasting ability for the last half-hour return. This type of

analysis of intraday momentum has been extended to several other markets, including the Chinese equity market (e.g., Zhang et al., 2019), foreign exchange market (e.g., Elaut et al., 2018), Chinese commodity futures market (e.g., Jin et al., 2020), and US crude oil exchange-traded fund (ETF) market (e.g., Wen et al., 2020).[1] In this paper, we extend this embryonic line of research to the patterns of intraday return predictability for several commodity ETFs and their related volatility indices, focusing on the crude oil, gold, and silver markets. This study explores intraday trading in commodity markets, which is of great importance to the growing finance research community, and day and high-frequency traders in particular.

We are motivated to analyse the existence and patterns of intraday momentum in the set of commodity ETFs and their corresponding indices for two reasons. First, even though there is a large body of literature on momentum, most of which focuses on cross-sectional momentum (e.g., Jegadeesh and Titman, 1993), and time-series momentum (e.g., Moskowitz et al., 2012; Neely et al., 2014), the existing research into time-series momentum within a trading day is quite limited, as is

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the study of intraday momentum in commodity markets. Second, we investigate whether, and to what extent, intraday momentum exists in commodity volatility indices, an unexplored area of research. The Chicago Board Options Exchange (CBOE) provides a set of commodity market volatility indices which are calculated by applying the model-free VIX methodology to the specific commodity ETF options.[2] Even though volatility indices themselves cannot be traded directly, trading can be made through a portfolio of options which replicates the performance of the volatility index.[3] Along with the prosperity of high-frequency trading in option markets, our analysis provides great practical implications for day trading of commodity options. Overall, we contribute to the growing body of literature on intraday momentum by extending it to several commodity ETFs and related volatility indices, and thus increasing the understanding of day trading in commodity ETFs and option markets.

Our empirical analysis provides several remarkable findings. First, distinctive patterns of intraday return predictability are identified in various commodity markets, where efficient predictors are intraday returns in various half-hour intervals, depending on the specific market. This finding is in sharp contrast to previous studies of the equity market, where the first half-hour returns are found to be the major predictor, and highlights the essential differences across the commodity markets. Out-of-sample (OOS) analysis confirms the significant performance of the intraday predictors. Second, the forecasting ability of the efficient predictor in each market generally rises with the volatility level in the first half-hour interval. Specifically, if we divide the sample into two subgroups based on volatility, intraday momentum in the high-volatility group tends to be stronger, demonstrated by a higher t-statistic of the predictor's coefficient. In addition, we explore the impacts of jump variation, the discontinuous component of the realized volatility, on the pattern of intraday momentum. We find that the intraday return predictability rises with the magnitude of jumps in the first half-hour interval. In summary, the intraday momentum is stronger on days of higher volatility and larger jumps in the first half-hour interval.

The empirical findings are supported by two theoretical explanations, the model of infrequent portfolio rebalancing (Bogousslavsky, 2016) and later-informed investors (Cushing and Madhavan, 2000). The theoretical model of Bogousslavsky (2016) shows that some investors balance their portfolios infrequently due to slow-moving capital, which leads to the positive correlation between the predictive half-hour return earlier in the day and its last half-hour counterpart the same day. The other theoretical model that can explain our results involves the presence of late-informed investors who access and process market information more slowly than others, and thus have to wait to trade at the end of the trading day (Cushing and Madhavan, 2000). Since the trading directions between the early- and late-informed traders are the same, a positive correlation emerges.

Substantial economic value can be generated by the market timing strategy, which is constructed based on the sign of the efficient intraday predictor. The market timing strategy outperforms the benchmark always-long strategy by generating a higher average return, higher Sharpe ratio, and higher success rate. The outperformance remains valid across all commodity ETFs and volatility indices, confirming the economic significance of the intraday momentum and providing practical implications for day traders.

Our paper makes contributions in several aspects. First, we comprehensively analyse the intraday momentum in several commodity

ETF markets, namely the crude oil, gold, and silver markets, where gold and silver are the major precious metal markets and crude oil is the major energy commodity. Thus, our study contributes to a full-around analysis of intraday momentum in commodity markets. Second, our data sample contains volatility indices of three commodities, the CBOE crude oil volatility index (i.e., OVX), CBOE gold volatility index (i.e., GVZ), and CBOE silver ETF volatility index (i.e., VXSLV). In sharp contrast to the increasing popularity of volatility products, research about their intraday trading patterns is very limited. Our research contributes by exploring the intraday pattern of commodity volatility indices, and confirms the existence of intraday momentum. Notably, even though the volatility indices themselves are not directly tradable, the availability of high-frequency option data makes the replication of volatility indices available, and thus our study has great practical implications. Overall, our empirical findings add to the limited literature on intraday momentum in commodity markets and volatility indices, and provide in-depth insight for policymakers and market practitioners about high-frequency trading.

The rest of the paper is structured as follows. Section 2 presents the empirical analysis, including data description, in-sample (IS) and OOS analysis for the intraday momentum in various markets, and two possible theoretical explanations. Section 3 evaluates the economic significance of the intraday momentum from the perspective of market timing. Section 4 concludes the paper.

## 2. Empirical analysis

### 2.1. Data description

In this paper, we focus on three pairs of commodity ETFs and their corresponding volatility indices, namely, the United States Oil Fund (i.e., USO) and its volatility index (i.e., OVX), SPDR Gold Shares (i.e., GLD) and its volatility index (i.e., GVZ), and iShares Silver Trust (i.e., SLV) and its volatility index (i.e., VXSLV).[4] The motivation for choosing these three commodities is as follows. Firstly, the high frequency price data on crude oil, gold, and silver and their implied volatility indices are obtained based on the data availability. Secondly, the three selected commodities are good representatives of two different types of commodities, energy and metals. Thirdly, the pairs of returns and volatility for each of the three commodities (crude oil, gold, and silver) can be used within a comparative analysis. All the sample data are 1-min high-frequency and extracted from Thomson Reuters Data Scope Select. Information such as bid and ask prices, number of trades, and trading volume is provided. Since the commodity ETFs and their volatility indices were launched at different times, we try to include datasets as large as possible for a comprehensive analysis, and thus the sample periods vary. Specifically, USO spans January 3, 2007 to July 31, 2019, OVX spans July 16, 2008 to June 28, 2019; GLD spans November 8, 2004 to May 30, 2019; GVZ spans May 1, 2009 to June 28, 2019; SLV spans May 1, 2006 to May 18, 2020; and VXSLV spans March 17, 2011 to April 30, 2020. We mainly focus on the predictability of intraday half-hour returns during the trading period (i.e., 9:30 a.m. to 16:00 p.m.), which are computed as differences of logarithmic prices as follows:

$$r_{i,t} = log(p_{i,t}) - log(p_{i-1,t}), i = 1, 2, \ldots, 13, \qquad (1)$$

where $p_{i,t}$ represents the prices of the $i$th half hour on trading day $t$, and there are 13 half-hour intervals for each trading day. Notably, the first half-hour return (i.e., $r_{1,t}$) is the logarithmic difference between the price $p_{1,t}$ at the end of first half hour on day $t$ and the price $p_{0,t}$ at market close of previous day $t-1$ (i.e., 16:00), thus, it contains the market

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**Table 1**
In-sample predictability: Crude oil market.

| | $r_1$ | $r_2$ | $r_3$ | $r_4$ | $r_5$ | $r_6$ | $r_7$ | $r_8$ | $r_9$ | $r_{10}$ | $r_{11}$ | $r_{12}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: USO** | | | | | | | | | | | | |
| Intercept | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | [1.06] | [0.84] | [0.89] | [0.77] | [0.76] | [0.87] | [0.82] | [0.86] | [0.86] | [0.76] | [0.92] | [0.85] |
| $\beta$ | **0.0118**\*\*\* | -0.009 | 0.0056 | -0.0152 | 0.0145 | 0.0112 | 0.0031 | -0.0091 | -0.0011 | 0.0142 | 0.0476 | -0.0042 |
| | **[2.86]** | [-0.71] | [0.55] | [-1.19] | [1.24] | [0.74] | [0.18] | [-0.64] | [-0.07] | [1.18] | [1.19] | [-0.09] |
| Obs. | 3166 | 3166 | 3,166 | 3166 | 3166 | 3166 | 3166 | 3166 | 3166 | 3166 | 3166 | 3166 |
| $R^2$(%) | 0.67 | 0.06 | 0.03 | 0.14 | 0.11 | 0.05 | 0 | 0.04 | 0 | 0.16 | 0.30 | 0 |
| **Panel B: OVX** | | | | | | | | | | | | |
| Intercept | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -0.0001 | 0 | 0 |
| | [-0.20] | [-0.27] | [-0.28] | [-0.26] | [-0.21] | [-0.23] | [-0.21] | [-0.24] | [-0.25] | [-0.34] | [-0.24] | [-0.24] |
| $\beta$ | -0.0014 | **0.0069**\*\* | -0.0024 | -0.0012 | 0.0107 | -0.0024 | 0.0274 | -0.0015 | 0.0046 | -0.0204 | **0.0589**\*\* | 0.0657 |
| | [-0.19] | **[2.00]** | [-0.63] | [-0.12] | [0.53] | [-0.09] | [0.71] | [-0.04] | [0.23] | [-0.61] | **[2.07]** | [1.53] |
| Obs. | 2758 | 2758 | 2758 | 2758 | 2758 | 2758 | 2758 | 2758 | 2758 | 2758 | 2758 | 2758 |
| $R^2$(%) | 0 | 0.10 | 0.01 | 0 | 0.02 | 0 | 0.12 | 0 | 0 | 0.08 | 0.25 | 0.28 |

Notes: This table shows the results of the in-sample predictability analysis for the crude oil market. Panel A and Panel B show the predictive results for USO and OVX, respectively. The numbers in brackets are Newey-West (1987) robust t-statistics, with 10%, 5%, 1% significance level denoted by \*, \*\*, \*\*\*, respectively.

information released overnight.

Descriptive statistics for the three commodity pairs, including crude oil, gold, and silver, are given in Appendix A (Tables A1, A2, and A3).

### 2.2. Intraday return predictability: In-sample (IS) analysis

In this section, we investigate the patterns of intraday return predictability in various markets. Most previous research into intraday momentum is confined to the role of the first half-hour returns (e.g., Gao et al., 2018; Zhang et al., 2019). We extend this to comprehensively investigate the predictability of all half-hour returns across the trading day. Specifically, we analyse whether earlier half-hour returns can forecast their counterparts near the market close on the same trading day, for the three pairs of commodity ETFs, crude oil, gold, and silver, and their related volatility indices. We conduct the IS analysis by implementing the following regression:

$$r_{13,t} = \alpha_i + \beta_i r_{i,t} + \varepsilon_{i,t}, t = 1, 2, \dots, T; i = 1, 2, \dots, 12, \qquad (2)$$

where $r_{i,t}$ denotes the $i$th half-hour returns.

Table 1 presents the predictive results for the crude oil pair, namely, the crude oil ETF (i.e., USO) and its volatility (i.e., OVX). For USO, the first half-hour returns significantly and positively predict the last half-hour returns, at the 1% significance level, which is consistent with previous findings in equity and crude oil markets. (e.g., Gao et al., 2018; Wen et al., 2020). In contrast, the intraday momentum pattern of OVX differs from that of the USO market, that is, the second and eleventh half-hour returns exhibit significantly positive predictability for the last half-hour returns at the 5% significance level, whereas the first half-hour returns exhibit nil forecasting ability. This result highlights the essential difference between the commodity ETF and its volatility index.

Table 2 shows the results for gold. For the gold ETF (i.e., GLD), the fifth half-hour returns exhibit significant and positive predictive power, with a t-statistic of 3.03 and an $R^2$ of 0.49%. For the gold volatility index (i.e., GVZ), the penultimate half-hour returns exhibit positive forecasting power, statistically significant at the 1% level. Overall, intraday momentum can be identified in gold ETF and volatility markets, however, they show different intraday predictive patterns.

Table 3 shows the results for silver. The intraday momentum pattern of the silver pair, that is, the silver ETF (i.e., SLV), and its related volatility index (i.e., VXSLV), shows that, for the former, the twelfth half-hour returns exhibit positive predictability, statistically significant at the 1% level. For the latter, the tenth half-hour returns show a significant and positive forecasting ability at the 5% significance level.

In summary, intraday return predictability exists in all the commodity ETFs and their related volatility index markets, however, the predictability pattern varies across markets. Our findings contribute to

the literature by identifying various patterns of intraday momentum in various markets, including commodity ETFs and their implied volatility indices. They add to studies dealing with stock markets (Gao et al., 2018; Zhang et al., 2019), foreign exchange markets (Elaut et al., 2018), and the crude oil ETF market (e.g., Wen et al., 2020). It is worth noting that all intraday predictors here yield much higher $R^2$ values than the typical low-frequency predictors, as pointed out by Rapach et al. (2010), which generally have low $R^2$.

### 2.3. Intraday return predictability: Out-of-sample analysis

So far, we have evaluated the IS predictability for the set of commodity ETFs and their corresponding volatility indices. In this section, we investigate the OOS forecasting performance of our model associated with Equation (2), because predictors with good IS performance may work poorly with OOS (e.g., Welch and Goyal, 2008). Note that we only focus on the OOS performance of the half-hour returns which show significant IS forecasting ability.

The statistic we employ for OOS evaluation is OOS R-square (i.e., $R_{OS}^2$), which measures the proportional reduction of the mean squared error associated with the predictive model relative to the historical mean model. Specifically, we split our sample data into two equal subsets, the first containing observations for IS analysis and the second containing the remaining $q$ ($q$ is almost equal to $m$) observations for OOS analysis. We apply the predictive model associated with Equation (2) to the first subset and then obtain estimated parameters $\hat{\alpha}_m$ and $\hat{\beta}_{1,m}$. The first OOS forecast (i.e., $\hat{r}_{13,m+1}$) can be computed as:

$$\hat{r}_{13,m+1} = \hat{\alpha}_m + \hat{\beta}_{i,m} r_{i,m+1}, \qquad (3)$$

where $r_{i,m+1}$ denotes the actual $i$th half-hour return on trading day m+1, and $\hat{r}_{13,m+1}$ represents the predicted last half-hour return for trading day $m+1$, estimated using the first m observations. We the expand the estimation window by adding one more observation and apply the new dataset to the predictive model. Based on the new set of estimated parameters (i.e., $\hat{\alpha}_{m+1}$ and $\hat{\beta}_{1,m+1}$), the second OOS forecast can be calculated as:

$$\hat{r}_{13,m+2} = \hat{\alpha}_{m+1} + \hat{\beta}_{i,m+1} r_{i,m+2}, \qquad (4)$$

where $r_{i,m+2}$ and $\hat{r}_{13,m+2}$ denote the actual $i$th half-hour return and predicted last half-hour return on trading day $m+2$, respectively. Finally, the OOS R-square (i.e. $R_{OS}^2$) can be expressed as:

**Table 2**
In-sample predictability: Gold market.

| | $r_1$ | $r_2$ | $r_3$ | $r_4$ | $r_5$ | $r_6$ | $r_7$ | $r_8$ | $r_9$ | $r_{10}$ | $r_{11}$ | $r_{12}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: GLD** | | | | | | | | | | | | |
| Intercept | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | [0.91] | [0.86] | [0.97] | [0.94] | [0.82] | [0.93] | [1.00] | [0.93] | [0.93] | [0.94] | [0.93] | [0.91] |
| $\beta$ | 0.0053 | 0.0119 | 0.0257 | -0.0114 | **0.0436***** | 0.0036 | -0.026 | 0.017 | 0.0107 | 0.0278 | -0.0064 | 0.0356 |
| | [1.28] | [0.78] | [1.40] | [-0.71] | **[3.03]** | [0.26] | [-1.10] | [0.74] | [0.37] | [1.17] | [-0.16] | [1.06] |
| Obs. | 3532 | 3532 | 3532 | 3532 | 3532 | 3532 | 3532 | 3532 | 3532 | 3532 | 3532 | 3532 |
| $R^2$(%) | 0.11 | 0.06 | 0.23 | 0.04 | 0.49 | 0.00 | 0.12 | 0.06 | 0.01 | 0.12 | 0.01 | 0.13 |
| **Panel B: GVZ** | | | | | | | | | | | | |
| Intercept | 0.0003* | 0.0003* | 0.0003* | 0.0003* | 0.0003* | 0.0003* | 0.0003* | 0.0003* | 0.0003* | 0.0003* | 0.0003* | 0.0002 |
| | [1.87] | [1.92] | [1.87] | [1.82] | [1.86] | [1.77] | [1.86] | [1.90] | [1.86] | [1.87] | [1.84] | [1.47] |
| $\beta$ | -0.0012 | -0.0141 | 0.007 | -0.0063 | 0.0032 | **-0.0521*** | -0.0069 | -0.0166 | -0.0089 | 0.0079 | **0.0506*** | **0.2031***** |
| | [-0.24] | [-0.88] | [0.31] | [-0.27] | [0.15] | **[-1.84]** | [-0.55] | [-0.75] | [-0.73] | [0.58] | **[1.86]** | **[5.21]** |
| Obs. | 2545 | 2545 | 2545 | 2545 | 2545 | 2545 | 2545 | 2545 | 2545 | 2545 | 2545 | 2545 |
| $R^2$(%) | 0 | 0.06 | 0.01 | 0.01 | 0.00 | 0.31 | 0.01 | 0.04 | 0.04 | 0.03 | 0.22 | 3.24 |

Notes: This table shows the results of the in-sample predictability analysis for the gold market. Panel A and Panel B show the predictive results for GLD and GVZ, respectively. The numbers in brackets are Newey-West (1987) robust t-statistics, with 10%, 5%, 1% significance level denoted by *, **, ***, respectively.

**Table 3**
In-sample predictability: Silver market.

| | $r_1$ | $r_2$ | $r_3$ | $r_4$ | $r_5$ | $r_6$ | $r_7$ | $r_8$ | $r_9$ | $r_{10}$ | $r_{11}$ | $r_{12}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: SLV** | | | | | | | | | | | | |
| Intercept | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | [0.19] | [0.01] | [0.29] | [0.19] | [0.16] | [0.20] | [0.26] | [0.20] | [0.20] | [0.21] | [0.18] | [0.16] |
| $\beta$ | 0.0001 | 0.0184 | 0.02 | -0.02 | 0.0173 | 0.0051 | -0.0245 | 0.0047 | 0.0178 | 0.0272 | -0.0132 | **0.1260***** |
| | [0.13] | [1.23] | [1.09] | [-1.43] | [1.29] | [0.24] | [-1.02] | [0.70] | [0.56] | [1.03] | [-0.29] | **[3.03]** |
| Obs. | 3537 | 3537 | 3537 | 3537 | 3537 | 3537 | 3537 | 3537 | 3537 | 3537 | 3537 | 3537 |
| $R^2$(%) | 0 | 0.14 | 0.15 | 0.13 | 0.09 | 0.01 | 0.13 | 0.02 | 0.05 | 0.10 | 0.02 | 1.72 |
| **Panel B: VXSLV** | | | | | | | | | | | | |
| Intercept | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | [-0.59] | [-0.40] | [-0.40] | [-0.46] | [-0.50] | [-0.41] | [-0.40] | [-0.41] | [-0.41] | [-0.36] | [-0.45] | [-0.39] |
| $\beta$ | 0.0072 | -0.0006 | -0.0009 | -0.012 | -0.0225 | -0.0033 | 0.0054 | -0.0087 | -0.0261 | **0.0276*** | -0.0277 | 0.0639 |
| | [1.27] | [-0.04] | [-0.03] | [-0.53] | [-0.67] | [-0.15] | [0.44] | [-0.47] | [-1.16] | **[1.96]** | [-0.48] | [1.41] |
| Obs. | 2296 | 2296 | 2296 | 2296 | 2296 | 2296 | 2296 | 2296 | 2296 | 2296 | 2296 | 2296 |
| $R^2$(%) | 0.15 | 0 | 0 | 0.03 | 0.09 | 0 | 0.01 | 0.01 | 0.16 | 0.22 | 0.08 | 0.39 |

Notes: This table shows the results of the in-sample predictability analysis for the silver market. Panel A and Panel B show the predictive results for SLV and VXSLV, respectively. The numbers in brackets are Newey-West (1987) robust t-statistics, with 10%, 5%, 1% significance level denoted by *, **, ***, respectively.

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T}\left(r_{13,t} - \widehat{r}_{13,t}\right)^2}{\sum_{t=1}^{T}\left(r_{13,t} - \overline{r}_{13,t}\right)^2}, \tag{5}$$

where $\widehat{r}_{13,t}$, $\overline{r}_{13,t}$, and $r_{13,t}$ denote the predicted value, average value, and real value of the last half-hour return on trading day $t$, respectively; $m$ and $T$ represent the number of observations of the initial subset for IS estimation and the total dataset. If $R^2_{OS} > 0$, it indicates that the predictive model outperforms the historical average model, and vice versa (Campbell and Thompson, 2008).

Table 4 shows the OOS results, with Panel A, B and C related to the crude oil, gold, and silver markets, respectively. We only test the OOS performance of efficient predictors in each market, namely, $r_1$ of crude oil ETF (i.e., USO), $r_2$ and $r_{11}$ of crude oil volatility (i.e., OVX), $r_5$ of gold ETF (i.e., GLD), $r_{12}$ of gold volatility (i.e., GVZ), $r_{12}$ of silver ETF (i.e., SLV) and $r_{10}$ of silver volatility (i.e., VXSLV). Panel A of Table 4 shows that for USO, the value of $R^2_{OS}$ is 0.80%, indicating that the predicator $r_1$ is still efficient for OOS analysis and works better than its historical average counterpart. However, for OVX, $r_{11}$ retains predictive efficiency, with $R^2_{OS}$ of 0.33%, but $r_2$ does not work well OOS, since its $R^2_{OS}$ has a negative value of -0.67%. Panel B shows that in the gold market, the fifth half-hour return (i.e., $r_5$) of GLD and the penultimate half-hour return of GVZ (i.e., $r_{12}$) exhibit significant OOS predictability, demonstrated by positive $R^2_{OS}$ with values of 0.26% and 0.53%, respectively. Panel C also confirms the validity of intraday predictors of SLV (i.e. $r_{12}$) and VXSLV (i.e., $r_{10}$) by positive $R^2_{OS}$, with values of 0.18% for the former

and 0.16% for the latter. Overall, most IS predictors continue to work well OOS, with the only expectational case being $r_2$ of OVX, which is not efficient for OOS analysis.

### 2.4. Impacts of volatility and jumps

Previous studies have found that intraday predictability tends to be stronger during highly volatile periods in equity and commodity markets (e.g., Gao et al., 2018; Jin et al., 2020; Wen et al., 2020; Zhang et al., 2019). In light of this, in this section we investigate whether volatility impacts the intraday momentum pattern shown by the commodity ETFs and their related volatility indices. Specifically, we split the data sample into two subsets based on the realized volatility in the half-hour interval, and further analyse the intraday return predictability pattern for each subgroup.[5]

For the crude oil ETF (i.e., USO), as presented in Panel A of Table 5, for the high-volatility subgroup the slope of the predictor (i.e., $r_1$) is 0.0118 with a t-statistic of 2.74, whereas its counterpart for the low-volatility subgroup is 0.0143 with a t-statistic of 1.98. The results indicate that intraday momentum is stronger for the high-volatility subgroup, since both the magnitude and t-statistic of the slope are larger. For crude oil volatility (OVX), the difference between the high- and low-volatility subgroups is even larger; the slope of the predictor (i.e. $r_{11}$) for

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[5] For details of volatility construction, please check Appendix B.1.

**Table 4**
Out-of-sample predictability.

| Panel A: Crude oil | | | |
|---|---|---|---|
| | USO | OVX | |
| | $r_1$ | $r_2$ | $r_{11}$ |
| Intercept | 1.42E-05 | 1.00E-05 | 1.00E-04 |
| t-stat | [15.59] | 3.97 | 8.05 |
| $\beta$ | 0.01 | 0.01 | 0.06 |
| t-stat | [71.66] | 10.62 | 30.92 |
| $R^2_{OS}$(%) | **0.38** | -0.67 | **0.33** |
| **Panel B: Gold** | | | |
| | GLD | GVZ | |
| | $r_5$ | $r_{12}$ | |
| Intercept | 1.12E-05 | -4.88E-06 | |
| t-stat | [12.42] | -0.46 | |
| $\beta$ | 0.04 | 0.11 | |
| t-stat | [108.04] | 23.85 | |
| $R^2_{OS}$(%) | **0.26** | **2.53** | |
| **Panel C: Silver** | | | |
| | SLV | VXSLV | |
| | $r_{12}$ | $r_{10}$ | |
| Intercept | 1.09E-05 | 1.71E-05 | |
| t-stat | [7.00] | 1.76 | |
| $\beta$ | 0.16 | 0.04 | |
| t-stat | [79.36] | 45.63 | |
| $R^2_{OS}$(%) | **0.18** | **0.16** | |

Notes: This table shows the results of the out-of-sample predictability analysis; if the $R^2_{OS}$ is positive, it shows good OOS predictive performance.

**Table 5**
Impacts of volatility on intraday momentum.

| Panel A: Crude oil | | | | |
|---|---|---|---|---|
| | USO | | OVX | |
| | High | Low | High | Low |
| Intercept | 0.0001 | 0 | 0 | -0.0001 |
| t-stat | [1.58] | [-0.70] | [0.00] | [-0.47] |
| $\beta$ | **0.0118*** | **0.0143** | **0.0900** | 0.0021 |
| t-stat | [2.74] | [1.98] | [2.28] | [0.05] |
| Obs. | 1583 | 1583 | 1380 | 1378 |
| $R^2$(%) | 0.80 | 0.34 | 0.75 | 0.00 |
| **Panel B: Gold** | | | | |
| | GLD | | GVZ | |
| | High | Low | High | Low |
| Intercept | 0 | 0 | 0 | 0 |
| t-stat | [0.68] | [0.21] | [-0.38] | [0.85] |
| $\beta$ | **0.0591*** | 0.0084 | **0.1447*** | 0.0638 |
| t-stat | [2.82] | [0.44] | [2.76] | [1.60] |
| Obs. | 1666 | 1583 | 1770 | 1767 |
| $R^2$(%) | 0.73 | 0.02 | 2.30 | 0.42 |
| **Panel C: Silver** | | | | |
| | SLV | | VXSLV | |
| | High | Low | High | Low |
| Intercept | 0 | 0 | 0.0001 | -0.0002 |
| t-stat | [-0.38] | [0.85] | [0.33] | [-0.71] |
| $\beta$ | **0.1447*** | 0.0638 | **0.0381** | 0.023 |
| t-stat | [2.76] | [1.60] | [1.97] | [1.21] |
| Obs. | 1770 | 1767 | 1148 | 1148 |
| $R^2$(%) | 2.30 | 0.42 | 0.37 | 0.16 |

Notes: This table shows the results of the impacts of realized volatility (RV) on the intraday predictability. RV in the first half-hour interval is calculated using the 1-min return including the overnight return. For each case, the whole sample is split into two subsets based on the first half-hour RV, and the predictor's performance is checked in each sub-sample. The numbers in brackets are Newey-West (1987) robust t-statistics, with 10%, 5%, 1% significance level denoted by *, **, ***, respectively.

GVZ) are highly significant at the 1% level when volatility is high, whereas both tend to be insignificant when volatility is low. Similar results hold for the silver market; when the market volatility is high, the coefficient for the predictor of silver ETF (i.e., SLV) is significant at the 1% level with a value of 0.1447, and the coefficient for the predictor of the silver volatility index (i.e., VXSLV) is 0.0381, statistically significant at the 5% level; when the market volatility is low, both predictors become insignificant. In summary, the intraday return predictability tends to be significant when volatility is high across all markets, suggesting the substantial influence of market volatility.

Jump variation, defined as the discontinuous component of realized volatility, is usually associated with large changes over a short period of time.[6] We investigate whether the impacts of volatility on intraday momentum originate from its discontinuous or continuous components. To achieve this, we divide our data into two subsets according to the magnitude of jump sizes in the first half-hour interval, and compare the performance of the predictors in each subgroup. Table 6 shows the results associated with jump impacts on intraday return predictability. In general, the predictability increases with the jump size, demonstrated by the significance level. Taking the gold volatility index (i.e., GVZ) as an example, for the high-volatility subgroup, the coefficient of the predictor is 0.2107, with a t-statistic of 4.88 and $R^2$ of 3.62%; whereas for the low-volatility subgroup, the predictability weakens a great deal, since the coefficient of the predictor is 0.1674, with a decreased t-statistic of 1.89 and $R^2$ of 1.85%. Likewise, for the crude oil ETF (i.e., USO), the t-statistic of the predictor slope is 2.77 for the high-volatility group, but

**Table 6**
Impacts of jump sizes on intraday momentum.

| Panel A: Crude oil | | | | |
|---|---|---|---|---|
| | USO | | OVX | |
| | High | Low | High | Low |
| Intercept | 0.0001 | 0 | 0.0001 | -0.0003 |
| t-stat | [1.20] | [-0.03] | [0.57] | [-1.13] |
| $\beta$ | **0.0120*** | 0.0083 | **0.0720*** | 0.036 |
| t-stat | [2.77] | [0.68] | [1.73] | [0.79] |
| Obs. | 2438 | 728 | 1698 | 1060 |
| $R^2$(%) | 0.79 | 0.10 | 0.41 | 0.08 |
| **Panel B: Gold** | | | | |
| | GLD | | GVZ | |
| | High | Low | High | Low |
| Intercept | 0 | 0.0001 | 0.0001 | 0.0006* |
| t-stat | [0.00] | [1.48] | [0.77] | [1.75] |
| $\beta$ | **0.0400** | **0.0427*** | **0.2107*** | **0.1674*** |
| t-stat | [2.22] | [1.77] | [4.88] | [1.89] |
| Obs. | 2376 | 873 | 1961 | 597 |
| $R^2$(%) | 0.35 | 0.57 | 3.62 | 1.85 |
| **Panel C: Silver** | | | | |
| | SLV | | VXSLV | |
| | High | Low | High | Low |
| Intercept | 0 | 0 | -0.0003 | 0.0002 |
| t-stat | [-0.09] | [0.62] | [-1.39] | [0.98] |
| $\beta$ | **0.1310*** | 0.1038 | 0.0137 | 0.0626 |
| t-stat | [2.78] | [1.52] | [1.00] | [1.63] |
| Obs. | 2734 | 803 | 1368 | 928 |
| $R^2$(%) | 1.87 | 1.14 | 0.06 | 0.86 |

Notes: This table shows the results of the impacts of the jump in the first half-hour interval on the intraday predictability. The jump in the first half-hour interval is calculated using the 1-min return including the overnight return. For each ETF, the whole sample is split into two quintiles based on the first half-hour jump, and then the last half-hour return is run on the half-hour return concerned using each sub-sample. The numbers in brackets are Newey-West (1987) robust t-statistics, with 10%, 5%, 1% significance level denoted by *, **, ***, respectively.

the former has a value of 0.0900, statistically significant at the 5% level, whereas the slope of the latter is insignificant with a t-statistic of 0.05. Panel B of Table 5 shows the results relating to the gold market. The intraday predictors of gold ETF (i.e., GLD) and gold volatility index (i.e.,

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[6] For details of jump construction, please check Appendix B.1.

decreases to 0.68 for the low-volatility group, which suggests that high intraday predictability is related to larger jumps in the first half-hour interval. For the other cases, such as the oil volatility index (i.e., OVX), gold ETF (i.e., GLD), and silver EFT (i.e., SLV), the t-statistics of the predictors decrease along with jump sizes. Notably, the only exceptional case is the silver volatility index (i.e., VXSLV), where the predictors of both subsamples become insignificant, which suggests that the driving force of intraday predictability of the silver volatility index may be related to the continuous component of realized volatility.

### 2.5. Theoretical explanations

Both the IS and OOS analyses confirm the existence of intraday momentum in all the commodity ETFs and their relative volatility indices, even though the predictors are different half-hour returns earlier in the trading day. In this section, we provide a brief discussion about the economic mechanism driving the intraday predictability by referring to previous literature such as Gao et al. (2018) and Zhang et al. (2019). The first theoretical explanation relates to the infrequent portfolio rebalancing model of Bogousslavsky (2016), which demonstrates theoretically that some traders tend to delay their portfolio rebalancing till the market close instead of trading instantaneously when the profitable signal is released, which results in the positive correlation. Important research by Duffie (2010) emphasizes the impacts of slow-moving capital and infrequent decisions made by investors. The second explanation relates to the presence of late-informed investors. Because of different speeds of information transmission and processing, some investors react more slowly than others. Consequently, these late-informed traders prefer to take action in the last half hour, since it is one of the most liquid periods, thus generating the positive correlation.

### 2.6. Discussion: Simulated financial markets

Based on no-arbitrage condition and efficient market hypothesis, there is a strand of literature analyzing the financial markets using simulated financial data (e.g., Rieger et al., 2011). Following this strand of literature (Cootner, 1962), we assume the prices of commodity ETFs follow the Random walk process. Notably, the Random Walk assumption implicitly guarantees the Efficient Market Hypothesis. Then, we further check the intraday return predictability pattern within a trading day. The results, reported in Table 7, show no evidence of intraday predictability based on the simulated financial data. One possible reason for this finding is that the Random Walk process cannot meet the price dynamics of commodity ETFs.

### 3. Economic value

In this section, we assess the economic values of the intraday predictors in each market from the perspective of market timing. According to the market timing strategy, the intraday trading sign is built upon the sign of the predictor, which is the specific half-hour return exhibiting significantly predictability.

We take a long (short) position in the market at the beginning of the last trading half-hour interval, if the predictor has positive (negative) value, and then clear the position when the market closes. Consequently, the payoff of the market timing strategy on trading day $t$ with predictor being the $i$th half-hour return (i.e., $r_i$) can be expressed as:

$$y(r_i) = \{ r_{13}, if \ r_i > 0, -r_{13}, if \ r_i \leq 0.$$

The benchmark trading strategy for comparison is the always-long strategy, which indicates that a long position is taken at beginning of the last half-hour interval and then a closed position at the end of the trading session. Table 8 shows the summary statistics of the payoffs generated by the market timing strategy as well as the always-long strategy. Alongside the typical summary statistics of average return and Sharpe ratio, we also report the success rate, which is defined as the proportion of trading days with nonnegative payoffs. Compared to the benchmark strategy, the market timing strategy generates higher average return, higher Sharpe ratio, and equivalent or higher success rate across all six markets, suggesting that intraday return predictability can generate substantial economic value from the market timing perspective. Taking the performance of market timing strategy and always-long strategy in the gold volatility index (i.e., GVZ) as an example, the average return for the former is 26.96%, much higher than that of the latter, with the value of 7.82%; the Sharpe ratios of the two strategies, the average returns scaled by the standard deviation, are 34.16 and 9.82, respectively, with the former almost 4 times the latter; and the success rate of the market timing strategy is 59%, slightly higher than the 54% reported for the benchmark.

### 4. Conclusion

In this paper, we provide evidence of the existence of various patterns of intraday momentum in commodity ETFs and their related volatility indices. Specifically, results show that the last half-hour returns can be predicted by returns of the earlier half-hour trading session, and that the predictor of each market differs. Accordingly, past half trading hours matter for intraday momentum but the informational contents of past half trading hours for intraday momentum are not alike in each market. Notably, the intraday return predictability seems to remain statistically significant for both IS and OOS analysis. During days of higher volatility and larger jumps, the intraday momentum is stronger across all the markets under study. Moreover, the intraday momentum shows economic significance from a market timing perspective. A market timing trading strategy based on the sign of intraday predictors outperforms the benchmark strategy in terms of average return, Sharpe ratio, and success rate. Theoretically, the intraday momentum is supported by the presence of investors who infrequently balance portfolios or who are late-informed of market information.

The empirical findings have crucial practical implications. It is important for high-frequency traders to pay attention to the intraday momentum by identifying the pattern of intraday predictability in various markets before assessing its economic value. In fact, our findings provide a strong reason for day traders in some specific commodity markets (e.g., the crude oil ETF) to postpone trading until the last half hour of trading. In doing so, they can learn information from the first half hour of trading to exploit evidence of intraday return predictability

**Table 7**
Intraday predictability using the simulated data.

| | $r_1$ | $r_2$ | $r_3$ | $r_4$ | $r_5$ | $r_6$ | $r_7$ | $r_8$ | $r_9$ | $r_{10}$ | $r_{11}$ | $r_{12}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.0629*** | 0.0809*** | 0.0805*** | 0.0796*** | 0.0811*** | 0.0784*** | 0.0818*** | 0.0812*** | 0.0783*** | 0.0820*** | 0.0783*** | 0.0787*** |
| | [15.87] | [56.46] | [54.94] | [55.50] | [53.74] | [49.64] | [55.54] | [54.49] | [50.99] | [52.46] | [56.15] | [52.21] |
| $\beta$ | 0.0802 | -0.0012 | -0.0012 | 0.0014 | -0.0047 | 0.0091 | -0.0111 | -0.0085 | 0.0147 | -0.0183 | 0.0178 | 0.016 |
| | [0.32] | [-0.57] | [-0.34] | [0.28] | [-0.69] | [1.05] | [-1.16] | [-0.76] | [1.13] | [-1.24] | [1.22] | [0.92] |
| Obs. | 3000 | 3000 | 3000 | 3000 | 3000 | 3000 | 3000 | 3000 | 3000 | 3000 | 3000 | 3000 |
| $R^2$(%) | 0.06 | 0.01 | 0.00 | 0.00 | 0.02 | 0.04 | 0.04 | 0.02 | 0.05 | 0.06 | 0.05 | 0.03 |

Notes: This table shows the results of the in-sample predictability analysis using the simulated data. The numbers in brackets are Newey-West (1987) robust t-statistics, with 10%, 5%, 1% significance level denoted by *, **, ***, respectively.

**Table 8**
Market timing strategy.

| | | Mean | T-stat | Std dev. | Sharpe ratio | Skewness | Kurtosis | Success rate |
|---|---|---|---|---|---|---|---|---|
| **Panel A: Crude oil** | | | | | | | | |
| USO | Market timing | 2.00 | 2.16 | 0.21 | 9.68 | 0.06 | 14.43 | 0.58 |
| | Always-long | 0.80 | 0.86 | 0.21 | 3.85 | 0.86 | 14.36 | 0.58 |
| OVX | Market timing | 7.09 | 1.65 | 0.89 | 7.93 | -0.06 | 69.47 | 0.55 |
| | Always-long | -1.04 | -0.24 | 0.89 | -1.16 | 4.32 | 69.41 | 0.49 |
| **Panel B: Gold** | | | | | | | | |
| GLD | Market timing | 0.81 | 1.23 | 0.15 | 5.43 | -1.11 | 31.50 | 0.53 |
| | Always-long | 0.52 | 0.79 | 0.15 | 3.48 | -1.56 | 31.47 | 0.52 |
| GVZ | Market timing | 26.96 | 6.86 | 0.79 | 34.16 | 1.36 | 16.72 | 0.59 |
| | Always-long | 7.82 | 1.97 | 0.80 | 9.82 | -0.44 | 17.05 | 0.54 |
| **Panel C: Silver** | | | | | | | | |
| SLV | Market timing | 2.35 | 2.30 | 0.24 | 9.76 | 1.65 | 23.70 | 0.57 |
| | Always-long | 0.19 | 0.19 | 0.24 | 0.79 | -0.61 | 23.90 | 0.57 |
| VXSLV | Market timing | 6.08 | 1.65 | 0.70 | 8.66 | -0.20 | 16.72 | 0.58 |
| | Always-long | -1.53 | -0.41 | 0.70 | -2.17 | 0.66 | 16.68 | 0.52 |

Notes: This table shows the performance of the market timing strategy. We take a long (short) position at the beginning of the last half-hour interval if the predictive half-hour is positive (negative), and clear the positions at the market close on each trading day. As a benchmark, the always-long strategy takes a position at the at the beginning of the last half-hour interval regardless of the sign of the predictive half-hour return, and clears the position at the market close. In the table, the success rate is the ratio of the number of days when the strategy generates a positive return to the total number of trading days.

and make economic gains. This is especially relevant for high volatility days. Our study leads to several open research questions. First, a systematic theoretical model of day trading which incorporates intraday trading pattern, and risk factors is needed, which might explain the essential differences of intraday momentum patterns among various markets. Second, the connections and differences between high-frequency (e.g., intraday) and low-frequency (e.g., monthly or weekly) time-series momentum remain unexplored. Third, given that intraday momentum is found to be more pronounced during high volatility days, it would be interesting to consider the impact of the COVID-19 outbreak on intraday momentum. We leave all these questions open for future research.

## Author statement

Yahua Xu: Conceptualization; Methodology; Data curation; Formal analysis; Writing - original draft; Writing - review & editing.

Elie Bouri: Project administration; Validation; Writing - original draft; Writing - review & editing.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.resourpol.2020.101830.

## Appendix A

**Table A.1**
Descriptive statistics for half-hour returns: Crude oil market

| Variable | Obs | Mean | Std.Dev. | Min | Max | Skewness | Kurtosis | ADF-test |
|---|---|---|---|---|---|---|---|---|
| **Panel A: USO** | | | | | | | | |
| $r_1$ | 3166 | -0.07% | 1.44% | -7.72% | 7.46% | -0.3 | 5.27 | -56.19*** |
| $r_2$ | 3166 | 0.00% | 0.56% | -3.36% | 4.60% | 0.2 | 8.22 | -47.42*** |
| $r_3$ | 3166 | -0.02% | 0.59% | -5.05% | 5.09% | -0.28 | 10.38 | -47.88*** |
| $r_4$ | 3166 | -0.02% | 0.51% | -3.14% | 3.45% | -0.16 | 8.1 | -50.56*** |
| $r_5$ | 3166 | 0.02% | 0.47% | -2.42% | 3.72% | 0.54 | 8.54 | -48.75*** |
| $r_6$ | 3166 | -0.01% | 0.40% | -2.83% | 2.51% | -0.09 | 8.03 | -48.06*** |
| $r_7$ | 3166 | 0.02% | 0.39% | -2.57% | 3.37% | 0.34 | 11.96 | -50.90*** |
| $r_8$ | 3166 | 0.00% | 0.42% | -6.41% | 4.45% | -0.54 | 29.16 | -45.30*** |
| $r_9$ | 3166 | 0.01% | 0.43% | -3.04% | 4.78% | 0.64 | 14.11 | -48.19*** |
| $r_{10}$ | 3166 | 0.02% | 0.58% | -3.50% | 5.84% | 0.22 | 11.4 | -48.99*** |
| $r_{11}$ | 3166 | -0.01% | 0.24% | -2.55% | 2.82% | 0.24 | 24.2 | -49.10*** |
| $r_{12}$ | 3166 | 0.00% | 0.20% | -1.51% | 1.89% | 0.82 | 15.82 | -49.94*** |
| $r_{13}$ | 3166 | 0.00% | 0.21% | -1.32% | 1.76% | 0.86 | 14.36 | -54.32*** |
| **Panel B: OVX** | | | | | | | | |
| $r_1$ | 2758 | 0.47% | 3.60% | -43.92% | 29.34% | -0.28 | 17.31 | -51.09*** |
| $r_2$ | 2758 | 0.06% | 4.05% | -30.74% | 97.59% | 12.41 | 238.27 | -46.38*** |
| $r_3$ | 2758 | -0.28% | 4.16% | -95.76% | 68.47% | -9.42 | 229.12 | -47.02*** |
| $r_4$ | 2758 | -0.13% | 1.79% | -66.71% | 14.91% | -19.60 | 715.07 | -47.31*** |
| $r_5$ | 2758 | -0.05% | 1.06% | -7.87% | 10.84% | 0.84 | 15.57 | -45.48*** |
| $r_6$ | 2758 | -0.02% | 0.86% | -6.02% | 6.60% | 0.95 | 10.69 | -46.87*** |
| $r_7$ | 2758 | -0.02% | 1.14% | -6.52% | 41.47% | 18.05 | 649.90 | -42.64*** |

(*continued on next page*)

**Table A.1** (*continued*)

| Variable | Obs | Mean | Std.Dev. | Min | Max | Skewness | Kurtosis | ADF-test |
|---|---|---|---|---|---|---|---|---|
| $r_8$ | 2758 | 0.03% | 0.88% | -5.12% | 15.95% | 2.92 | 48.38 | -42.41*** |
| $r_9$ | 2758 | 0.01% | 1.05% | -10.90% | 17.31% | 3.04 | 51.42 | -44.82*** |
| $r_{10}$ | 2758 | -0.07% | 1.23% | -16.75% | 7.94% | -2.11 | 33.16 | -44.85*** |
| $r_{11}$ | 2758 | 0.00% | 0.75% | -4.72% | 6.91% | 1.24 | 14.49 | -43.80*** |
| $r_{12}$ | 2758 | 0.00% | 0.72% | -9.35% | 6.27% | -0.52 | 26.05 | -46.78*** |
| $r_{13}$ | 2758 | 0.00% | 0.89% | -5.51% | 15.25% | 4.32 | 69.41 | -45.79*** |

Note: This table presents the descriptive summary of the half-hour returns with t-statistics of the Augmented Dickey-Fuller test. ***, **, and * denote significance level at the 1%, 5%, and 10% level, respectively.

**Table A.2**
Descriptive statistics for half-hour returns: Gold market

| Variable | Obs | Mean | Std.Dev. | Min | Max | Skewness | Kurtosis | ADF-test |
|---|---|---|---|---|---|---|---|---|
| **Panel A: Gold** | | | | | | | | |
| $r_1$ | 3249 | -0.05% | 5.66% | -301.00% | 103.67% | -44.46 | 2501.03 | -378.56*** |
| $r_2$ | 3249 | 0.01% | 0.30% | -2.64% | 1.88% | -0.40 | 10.08 | -51.30*** |
| $r_3$ | 3249 | 0.00% | 0.27% | -2.04% | 2.68% | -0.17 | 13.25 | -50.16*** |
| $r_4$ | 3249 | 0.00% | 0.24% | -1.95% | 1.14% | -0.81 | 10.66 | -50.42*** |
| $r_5$ | 3249 | 0.01% | 0.23% | -1.80% | 1.84% | -0.38 | 11.66 | -51.16*** |
| $r_6$ | 3249 | 0.00% | 0.21% | -1.34% | 2.46% | 0.14 | 14.20 | -53.29*** |
| $r_7$ | 3249 | 0.01% | 0.20% | -2.17% | 2.78% | 0.79 | 24.02 | -55.14*** |
| $r_8$ | 3249 | 0.00% | 0.21% | -1.52% | 1.61% | -0.25 | 9.92 | -49.32*** |
| $r_9$ | 3249 | 0.00% | 0.16% | -1.83% | 1.85% | 0.12 | 23.46 | -52.76*** |
| $r_{10}$ | 3249 | 0.00% | 0.19% | -1.58% | 4.28% | 3.21 | 86.00 | -52.33*** |
| $r_{11}$ | 3249 | 0.00% | 0.16% | -1.26% | 1.39% | 0.31 | 17.99 | -51.10*** |
| $r_{12}$ | 3249 | 0.00% | 0.16% | -3.12% | 1.56% | -2.15 | 61.50 | -50.59*** |
| $r_{13}$ | 3249 | 0.00% | 0.15% | -2.31% | 1.16% | -1.56 | 31.47 | -56.91*** |
| **Panel B: GVZ** | | | | | | | | |
| $r_1$ | 2558 | -0.01% | 3.94% | -28.52% | 31.48% | 0.92 | 11.91 | -50.21*** |
| $r_2$ | 2558 | 0.06% | 1.34% | -22.61% | 8.97% | -1.09 | 38.28 | -42.43*** |
| $r_3$ | 2558 | -0.01% | 1.21% | -7.82% | 17.01% | 2.81 | 38.11 | -43.37*** |
| $r_4$ | 2558 | -0.05% | 1.04% | -7.42% | 8.12% | 0.78 | 11.69 | -41.14*** |
| $r_5$ | 2558 | -0.03% | 0.94% | -7.37% | 8.60% | 0.59 | 12.63 | -37.76*** |
| $r_6$ | 2558 | -0.03% | 0.85% | -5.86% | 5.98% | -0.08 | 10.05 | -41.54*** |
| $r_7$ | 2558 | -0.01% | 1.12% | -23.72% | 22.47% | -1.97 | 188.22 | -37.52*** |
| $r_8$ | 2558 | 0.02% | 0.94% | -11.35% | 10.41% | 0.59 | 23.27 | -41.24*** |
| $r_9$ | 2558 | -0.02% | 1.76% | -39.70% | 26.49% | -3.93 | 222.70 | -44.19*** |
| $r_{10}$ | 2558 | 0.00% | 1.76% | -30.83% | 43.68% | 1.30 | 259.95 | -45.53*** |
| $r_{11}$ | 2558 | 0.01% | 0.74% | -6.47% | 6.49% | 0.53 | 16.64 | -46.47*** |
| $r_{12}$ | 2558 | 0.04% | 0.70% | -4.58% | 6.20% | 0.97 | 14.15 | -43.85*** |
| $r_{13}$ | 2558 | 0.03% | 0.80% | -7.85% | 5.52% | -0.44 | 17.05 | -40.84*** |

Note: This table presents the descriptive summary of the half-hour returns with t-statistics of the Augmented Dickey-Fuller test. ***, **, and * denote significance level at the 1%, 5%, and 10% level, respectively.

**Table A.3**
Descriptive statistics for half-hour returns: Silver market

| Variable | Obs | Mean | Std.Dev. | Min | Max | Skewness | Kurtosis | ADF-test |
|---|---|---|---|---|---|---|---|---|
| **Panel A: SLV** | | | | | | | | |
| $r_1$ | 3537 | -0.08% | 4.19% | -229.75% | 6.88% | -46.89 | 2563.40 | -52.88*** |
| $r_2$ | 3537 | 0.04% | 0.49% | -3.12% | 2.90% | 0.06 | 7.55 | -51.88*** |
| $r_3$ | 3537 | -0.02% | 0.46% | -5.23% | 3.00% | -1.30 | 16.15 | -51.06*** |
| $r_4$ | 3537 | 0.00% | 0.43% | -4.53% | 3.98% | -0.75 | 16.25 | -52.92*** |
| $r_5$ | 3537 | 0.01% | 0.41% | -3.01% | 2.77% | -0.64 | 13.47 | -50.82*** |
| $r_6$ | 3537 | -0.01% | 0.36% | -5.68% | 3.04% | -1.04 | 28.64 | -50.90*** |
| $r_7$ | 3537 | 0.00% | 0.35% | -5.16% | 4.41% | 0.03 | 33.62 | -50.41*** |
| $r_8$ | 3537 | -0.01% | 0.70% | -4.05% | 35.57% | 36.70 | 1869.97 | -47.24*** |
| $r_9$ | 3537 | 0.00% | 0.30% | -8.73% | 4.01% | -6.62 | 223.32 | -44.80*** |
| $r_{10}$ | 3537 | 0.00% | 0.27% | -1.83% | 4.19% | 0.97 | 24.64 | -55.31*** |
| $r_{11}$ | 3537 | 0.00% | 0.25% | -1.97% | 2.38% | 0.38 | 16.19 | -53.20*** |
| $r_{12}$ | 3537 | 0.00% | 0.25% | -4.74% | 1.85% | -2.62 | 52.15 | -54.50*** |
| $r_{13}$ | 3537 | 0.00% | 0.24% | -2.43% | 2.97% | -0.61 | 23.90 | -56.88*** |
| **Panel B: VXSLV** | | | | | | | | |
| $r_1$ | 2296 | 0.44% | 3.80% | -25.21% | 45.50% | 1.67 | 19.85 | -51.98*** |
| $r_2$ | 2296 | -0.09% | 1.24% | -7.42% | 15.63% | 1.79 | 24.15 | -42.12*** |
| $r_3$ | 2296 | -0.06% | 1.10% | -5.42% | 15.06% | 2.50 | 29.73 | -41.81*** |
| $r_4$ | 2296 | -0.07% | 1.00% | -5.40% | 13.88% | 1.79 | 24.27 | -44.71*** |
| $r_5$ | 2296 | -0.07% | 0.92% | -7.17% | 12.97% | 1.95 | 29.61 | -35.60*** |
| $r_6$ | 2296 | -0.06% | 0.82% | -12.22% | 6.71% | -1.16 | 31.39 | -41.57*** |

**Table A.3** (*continued*)

| Variable | Obs | Mean | Std.Dev. | Min | Max | Skewness | Kurtosis | ADF-test |
|---|---|---|---|---|---|---|---|---|
| $r_7$ | 2296 | -0.02% | 1.10% | -25.82% | 25.47% | 0.03 | 258.76 | -39.57*** |
| $r_8$ | 2296 | 0.00% | 0.96% | -21.08% | 13.17% | -2.56 | 122.63 | -34.63*** |
| $r_9$ | 2296 | 0.00% | 1.09% | -11.39% | 32.28% | 10.93 | 349.99 | -42.34*** |
| $r_{10}$ | 2296 | -0.02% | 1.19% | -36.19% | 17.25% | -10.82 | 394.50 | -42.84*** |
| $r_{11}$ | 2296 | -0.03% | 0.74% | -3.86% | 14.19% | 3.36 | 69.14 | -39.85*** |
| $r_{12}$ | 2296 | 0.00% | 0.69% | -3.20% | 4.47% | 0.55 | 8.71 | -42.55*** |
| $r_{13}$ | 2296 | -0.01% | 0.70% | -6.13% | 6.60% | 0.66 | 16.68 | -41.40*** |

Note: This table presents the descriptive summary of the half-hour returns with t-statistics of the Augmented Dickey-Fuller test. ***, **, and * denote significance level at the 1%, 5%, and 10% level, respectively.

## Appendix B.1. Construction of volatility and jump measures

Following Barndorff-Nielsen and Shephard (2004), the realized volatility is calculated as:

$$RV_t = \sum_{k=1}^{n} r_{t,k}^2,$$

where $r_{t,k}$ is the $k$th 1-min return in the $t$th interval and n denotes the number of the observations. According to Barndorff-Nielsen and Shephard (2004) as well as to Huang and Tauchen (2005), the bipower variation (BV) is computed as:

$$BV_t = \frac{\pi}{2} \frac{n}{n-1} \sum_{k=2}^{n} |r_{t,k}||r_{t,k-1}|,$$

Then the statistic to measure the jump size during the sample period is defined as:

$$\widehat{J} = \sqrt{(RV_t - BV_t) \times I\left(ZJ_t \geq \Phi_{\tilde{\alpha}}^{-1}\right)},$$

Where

$$\mu_p = 2^{p/2} \frac{\Gamma[(p+1)/2]}{\Gamma[1/2]}, p > 0,$$

$$TP_t = m\mu_{4/3}^{-3} \frac{m}{m-2} \sum_{k=3}^{m} |r_{t,k-2}|^{4/3} |r_{t,k-1}|^{4/3} |r_{t,k}|^{4/3},$$

$$RJ_t = \frac{RV_t - BV_t}{RV_t},$$

$$ZJ_t = \frac{RJ_t}{\sqrt{\left\{(\pi/2)^2 + \pi - 5\right\}/m \times \max\left(1, TP_t/BV_t^2\right)}},$$

and $I$ is an indicative function where the value is 1 if the criterion is satisfied, otherwise 0, $\Phi_{\tilde{\alpha}}^{-1}$ is the inverse cumulative distribution function (CDF) of the standard normal distribution. $\Gamma$ is the gamma function, and the value of the *sign*() function takes the same sign as the argument. If the probability (i.e., $\tilde{\alpha}$) exceeds 99.9%, a jump is assumed to exist.

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